Question:

Process:

1. Follow the procedure mentioned in Chapter 4 – Training Linear Models to make it work on Colab.
2. Save the abalone_train.cvs to a local drive

- Note: the abalone_train.cvs has this format
  - names=["Length", "Diameter", "Height", "Whole weight", "Shucked weight", "Viscera weight", "Shell weight", "Age"])

3. Change the process mentioned in Step 1 by reading CVS test data from a local drive : abalone_train.cvs

- Process
  a. You can modify the code in Linear regression using the Normal Equation. Instead of reading random data

```
import numpy as np
X = 2 * np.random.rand(100, 1)
y = 4 + 3 * X + np.random.randn(100, 1)
```

You need to read data from a local drive and transfornm the data to fit the Python code.

```
import numpy as np
import pandas as pd

# X = 2 * np.random.rand(100, 1)
# y = 4 + 3 * X + np.random.randn(100, 1)
from google.colab import files
uploaded  = files.upload()

import io
abalone = pd.read_csv(
   io.BytesIO(uploaded['abalone_train.csv']),
   names=["Length", "Diameter", "Height", "Whole weight",
         "Shucked weight", "Viscera weight", "Shell
          weight", "Age"])
# X1 is
#    0      0.435
#    1      0.585
#    2      0.655
#    .....
X1 = abalone["Length"]

# X2 is
#    array([0.435, 0.585, ...., 0.45])
X2 = np.array(X1)
```

```
# X is
#    array([[0.435],
#          [0.585],
#          [0.655],
#          ...,
#          [0.53 ],
#          [0.395],
#          [0.45 ]])
X = X2.reshape(-1, 1)

y1 = abalone["Height"]
y2 = np.array(y1)
y = y2.reshape(-1, 1)
```

b. There is one more line you need to modify to make the complete process work.

Answer:

Go to Colab and set up

```python
# Python ≥3.5 is required
import sys
assert sys.version_info >= (3, 5)

# Scikit-Learn ≥0.20 is required
import sklearn
assert sklearn.__version__ >= "0.20"

# Common imports
import numpy as np
import os

# to make this notebook's output stable across runs
np.random.seed(42)

# To plot pretty figures
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

# Where to save the figures$
PROJECT_ROOT_DIR = "."
CHAPTER_ID = "training_linear_models"
IMAGES_PATH = os.path.join(PROJECT_ROOT_DIR, "images", CHAPTER_ID)
os.makedirs(IMAGES_PATH, exist_ok=True)

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=300):
    path = os.path.join(IMAGES_PATH, fig_id + "." + fig_extension)
    print("Saving figure", fig_id)
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)
```

```python
import numpy as np

X = 2 * np.random.rand(100, 1)
y = 4 + 3 * X + np.random.randn(100, 1)
from google.colab import files
uploaded  = files.upload()

import io
abalone = pd.read_csv(
    io.BytesIO(uploaded['abalone_train.csv']),
    names=["Length", "Diameter", "Height", "Whole weight", "Shucked weight",
           "Viscera weight", "Shell weight", "Age"])
# X1 is
#    0       0.435
#    1       0.585
#    2       0.655
#    .....
X1 = abalone["Length"]

# X2 is
#    array([0.435, 0.585, ...., 0.45])
X2 = np.array(X1)

# X is
#    array([[0.435],
#           [0.585],
#           [0.655],
#           ...,
#           [0.53 ],
#           [0.395],
#           [0.45 ]])
X = X2.reshape(-1, 1)

y1 = abalone["Height"]
y2 = np.array(y1)
y = y2.reshape(-1, 1)
```

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Add abalone_train.csv

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A1 | fx | 0.435

A	B	C	D	E	F	G	H
0.435	0.335	0.11	0.334	0.1355	0.0775	0.0965	7
0.585	0.45	0.125	0.874	0.3545	0.2075	0.225	6
0.655	0.51	0.16	1.092	0.396	0.2825	0.37	14
0.545	0.425	0.125	0.768	0.294	0.1495	0.26	16
0.545	0.42	0.13	0.879	0.374	0.1695	0.23	13
0.57	0.45	0.145	0.751	0.2825	0.2195	0.2215	10
0.47	0.36	0.13	0.472	0.182	0.114	0.15	10
0.61	0.45	0.19	1.0805	0.517	0.2495	0.2935	10
0.52	0.425	0.125	0.79	0.372	0.205	0.19	8
0.485	0.39	0.12	0.599	0.251	0.1345	0.169	8
0.625	0.495	0.155	1.025	0.46	0.1945	0.34	9
0.615	0.495	0.16	1.255	0.5815	0.3195	0.3225	12
0.455	0.35	0.14	0.5185	0.221	0.1265	0.135	10
0.475	0.355	0.115	0.5195	0.279	0.088	0.1325	7
0.385	0.3	0.1	0.2895	0.1215	0.063	0.09	7
0.67	0.525	0.165	1.6085	0.682	0.3145	0.4005	11
0.615	0.52	0.15	1.3435	0.629	0.2605	0.345	10
0.52	0.4	0.13	0.5825	0.233	0.1365	0.18	10
0.635	0.495	0.18	1.596	0.617	0.317	0.37	11
0.72	0.575	0.23	2.2695	0.8835	0.3985	0.665	16
0.57	0.435	0.15	0.8295	0.3875	0.156	0.245	10
0.725	0.575	0.24	2.21	1.351	0.413	0.5015	13
0.435	0.35	0.11	0.384	0.143	0.1005	0.125	13
0.685	0.55	0.2	1.7725	0.813	0.387	0.49	11
0.575	0.445	0.145	0.876	0.3795	0.1615	0.27	10
0.575	0.435	0.13	1.0105	0.368	0.222	0.32	10
0.625	0.445	0.16	1.09	0.46	0.2965	0.304	11
0.355	0.27	0.075	0.1775	0.079	0.0315	0.054	6
0.565	0.48	0.175	0.957	0.3885	0.215	0.275	18
0.47	0.365	0.12	0.582	0.29	0.092	0.146	8
0.41	0.325	0.105	0.3635	0.159	0.077	0.12	10
0.55	0.415	0.135	0.7635	0.318	0.21	0.2	9
0.575	0.435	0.14	0.8455	0.401	0.191	0.222	9
0.55	0.47	0.15	0.897	0.377	0.184	0.29	9
0.355	0.28	0.1	0.2275	0.0935	0.0455	0.085	11
0.58	0.45	0.155	0.8275	0.321	0.1975	0.2445	8
0.525	0.405	0.135	0.7575	0.3305	0.216	0.195	10
0.63	0.525	0.195	1.3135	0.4935	0.2565	0.465	10
0.465	0.36	0.125	0.4365	0.169	0.1075	0.145	11
0.63	0.495	0.18	1.31	0.495	0.295	0.4695	10
0.325	0.2	0.08	0.0995	0.0395	0.0225	0.032	8
0.645	0.5	0.16	1.3815	0.672	0.326	0.315	9
0.62	0.485	0.18	1.1785	0.4675	0.2655	0.39	13
0.495	0.375	0.155	0.976	0.45	0.2285	0.2475	9
0.645	0.52	0.17	1.197	0.526	0.2925	0.317	11

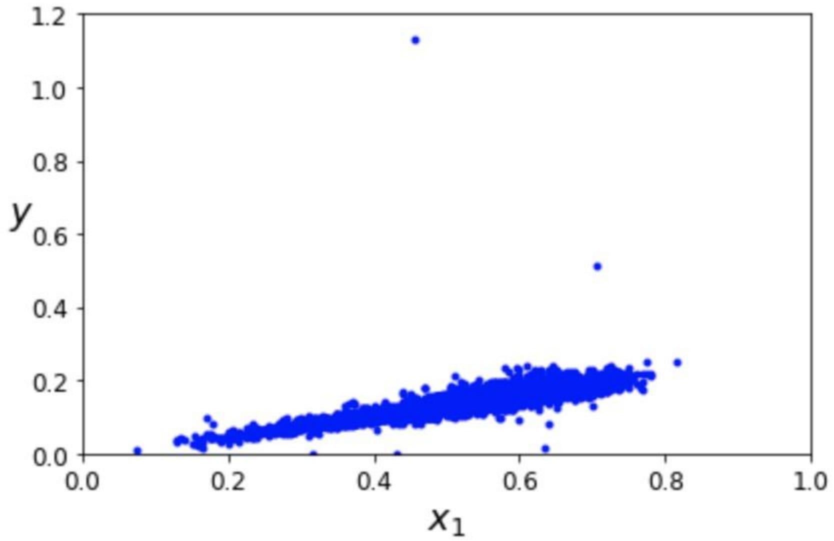
abalone_train

After successfully upload，then create data show

```
[ ]  plt.plot(X, y, "b.")
     plt.xlabel("$x_1$", fontsize=18)
     plt.ylabel("$y$", rotation=0, fontsize=18)
     plt.axis([0, 1, 0, 1.2])
     save_fig("generated_data_plot")
     plt.show()
```

The model will look like

```
Saving figure generated_data_plot
```



Get the linear regression equations' value and graph

```
[ ] X_b = np.c_[np.ones((X.size, 1)), X]  # add x0 = 1 to each instance
    theta_best = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).dot(y)
```

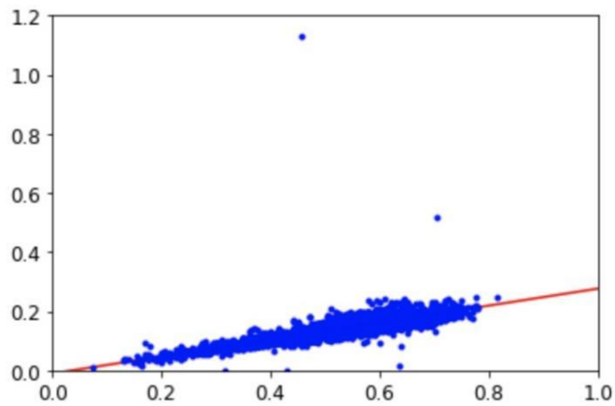
```
[ ] theta_best
```

```
array([[-0.0108267 ],
       [ 0.28716253]])
```

```
[ ] X_new = np.array([[0], [2]])
    X_new_b = np.c_[np.ones((2, 1)), X_new]  # add x0 = 1 to each instance
    y_predict = X_new_b.dot(theta_best)
    y_predict
```

```
array([[-0.0108267 ],
       [ 0.56349837]])
```

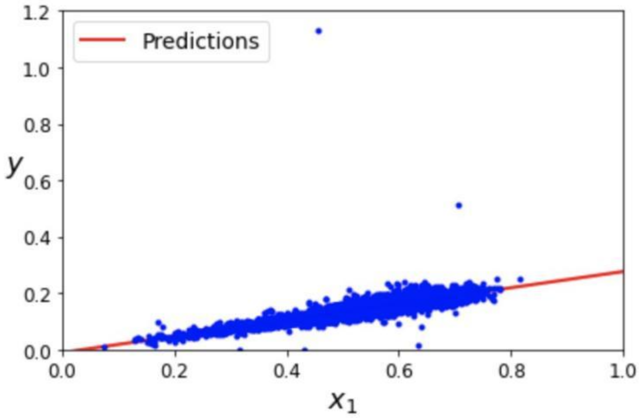
```
[ ] plt.plot(X_new, y_predict, "r-")
    plt.plot(X, y, "b.")
    plt.axis([0, 1, 0, 1.2])
    plt.show()
```



The figure in the book actually corresponds to the following code, with a legend and axis labels:

```
[ ] plt.plot(X_new, y_predict, "r-", linewidth=2, label="Predictions")
    plt.plot(X, y, "b.")
    plt.xlabel("$x_1$", fontsize=18)
    plt.ylabel("$y$", rotation=0, fontsize=18)
    plt.legend(loc="upper left", fontsize=14)
    plt.axis([0, 1, 0, 1.2])
    save_fig("linear_model_predictions_plot")
    plt.show()
```

```
Saving figure linear_model_predictions_plot
```




```
[ ] from sklearn.linear_model import LinearRegression

    lin_reg = LinearRegression()
    lin_reg.fit(X, y)
    lin_reg.intercept_, lin_reg.coef_
```

```
(array([-0.0108267]), array([[0.28716253]]))
```

```
[ ] lin_reg.predict(X_new)
```

```
array([[-0.0108267 ],
       [ 0.56349837]])
```

The `LinearRegression` class is based on the `scipy.linalg.lstsq()` function (the name stands for "least squares"), which you could call directly:

```
[ ] theta_best_svd, residuals, rank, s = np.linalg.lstsq(X_b, y, rcond=1e-6)
    theta_best_svd
```

```
array([[-0.0108267 ],
       [ 0.28716253]])
```

This function computes $\mathbf{X}^{+}\mathbf{y}$, where $\mathbf{X}^{+}$ is the *pseudoinverse* of $\mathbf{X}$ (specifically the Moore-Penrose inverse). You can use `np.linalg.pinv()` to compute the pseudoinverse directly:

```
[ ] np.linalg.pinv(X_b).dot(y)
```

```
array([[-0.0108267 ],
       [ 0.28716253]])
```